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A Signature-based Approach for Data-driven Analysis of the Inter-modal Demand Dynamics

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Abstract—Transport systems are prone to disruptions due to various factors, from extreme weather conditions to public transport failures and road accidents. These disruptions alter travel dynamics and affect expected travel time and cost, prompting passengers to cancel trips, wait for resolution, or change paths and mode. This paper aims to provide a data-driven methodology for gaining insights into how mode choice is affected by disruptions. First, we use multi-source data to form a unified multi-modal dataset of car, public transport, and bike-sharing demand data. Then, by introducing a signature range, we define an hourly range of expected demand. Utilising this signature range, we first detect hours with irregular demand in each mode and then proceed to spot instances where a potential inter-modal demand spillover has occurred. Finally, exploring our data from Lyon, France, we showcase examples of implementing our method to actual recorded data. Our study paves the way for more extensive studies on the inter-modal demand spillover and its management implications.

Index Terms—Transport disruption, Travel behaviour, Multi-modal mobility, Spillover

I. INTRODUCTION

The increasing accessibility of mobility data through smart public transport passes, GPS data, and shared mobility applications' data has opened novel doors for exploring urban mobility. As each mobility data source captures a specific side of urban travel (e.g. a particular mode), it is essential to integrate and jointly leverage such sources to form a more coherent analysis framework for multi-modal mobility [1].

Transport system disruptions jeopardise the transport level of service by increasing user's travel cost and time [2]. These disruptive events inflict complex effects on passengers' travel behaviour (e.g. trip cancellation, route change, or mode change). Thus, exploring these events can give us insights into passenger's responsive behaviour to external changes, be it minor perturbations or significant long-term changes [3].

As detailed in Sec. II, various data-driven methods from different scientific fields have been utilised for detecting and identifying anomalies. However, such studies are limited in addressing disruptions from single transportation modes' point of view. In the urban mobility context, a multi-modal perspective appears more appropriate as it could unveil the complex

and interrelated modal dynamics of travel behaviour through disruptive events. This dynamic relies on many factors, such as the nature of the disruption, its time, the affected transport modes and the properties of the network itself.

The demand spillover phenomena in the urban mobility context can be described as an excess of demand moving between modes of transport due to a sudden or incremental decrease in the original mode's capacity, or an increase in the original mode's demand. This paper aims to take an exploratory and empirical approach to investigate this multi-modal dynamic based on multi-source recorded data for the city of Lyon, France. Such a unique dataset is produced by merging the existing mobility data gathered by various sources from different transport operators in a uniform format. We rely on this merged dataset to develop a novel methodology for detecting network-wide anomalies in multi-modal travel demand. Afterwards, we study a few unique scenarios of transport disruptions where possible inter-modal demand spillover is observed. These scenarios include weather-induced disruptions, terrorist attacks, and large-scale public events. The contributions of our paper could be summarized as follows:

- Integration of multi-source travel demand data in order to target multi-modality in the empirical exploration of urban mobility under disruptions.
- A fine-grained automatic data-driven detection of disruptive events with inter-modal demand spillover potential, based on a signature-based anomaly detection method.

Understanding how the multi- and inter-modal dynamics of travel demand take form under distinct contextual structures of various disruptions will facilitate the management of short-term perturbations and provide insights into travellers' adaptability to disruptive events. The latter may also be valuable for policymakers as said insights shed light on the potential of planned interventions for desired modal shifts.

In the remaining sections of the paper, we first analyse, in Section II, related research on demand dynamics in presence of disruptions. Then, in Section III, we detail the data we use for this study. Following that, we construe our methodology in Section IV. Next, we showcase examples of results derived from our methods in Section V. Finally, we discuss our findings and future directions in Section VI.

II. RELATED WORK

When it comes to analysing the demand dynamics from a user perspective in the context of transport disruptions, the literature has often looked at this problem in a mono-modal manner, mostly taking road users into account. There are fundamental differences between car and public transport users, resulting in different dynamics of response to disruptions [4]. Consilvio *et al.* [5] argue that a multi-modal integration of different transport modes needs to be considered to manage transport network disruptions, stating that recovery strategies are adopted more smoothly in the integrated context.

Some papers have explored passengers' short-term travel behaviour responses to various disruptions. Zhu *et al.* (2017) [6] explore user responses to transit service disruptions using a survey-based method and observe the reactions to different disruptions. Budnitz *et al.* (2017) [7] survey the bus users' travel behaviour under weather-induced disruptions and remark that the demand for bus use decreases with precipitation; however, the scope of this decrease depends on the purpose of the initially planned trip. Zhang *et al.* (2022) [8] use mobile data to observe human mobility during two typhoons and conclude that while the movement of people reduces under extreme weather events, recurring trips tend to have weaker perturbations compared to a general average of trips. Lepage *et al.* (2020) [9] analyse the impact of activities, weather, and transport service disruptions on multi-modal demand and use statistical models to predict passenger behaviour through said contextual conditions. These studies use various forms of data and methodologies to analyse the users' responses to specific disruptions. However, a multi-modal, fully integrated and automated approach is absent from the literature in inspecting the demand dynamics through transport network perturbations.

Although rational preference and behavioural inertia play vital roles in passengers' mode choices during disruptive events [10], a significant change in transport supply can also lead to modal changes. Mainly, the studies have focused on the effects of the modal shift from public transport to cars in service disruptions [11]–[13]. While analysing demand dynamics through these events has relied chiefly on surveys, our data-driven approach can contribute to the current state of the art, as the possible difference between stated and observed preference remains an inherent shortcoming for travel behaviour surveys. Van Exel *et al.* [12] observe a 15% difference in responses to a survey regarding the mode choice in reaction to a rail strike before and after the event. The emphasis on the inter-modal demand spillover effects of transport disruptions has been absent from the literature. Only a few studies explore the demand dynamics of different modes during said disruptions. Li *et al.* [14] and Michaelides *et al.* [15] use Beijing and Athens' data, respectively, to analyse the demand response dynamics between public transport modes under specific shocks. They both observe the demand spillover phenomena within public transport modes. Saberi *et al.* (2018) [16] and Yang *et al.* (2022) [17] study the public transport demand spillover into shared-bike use during a metro strike and note

a considerable increase in shared bikes. The works mentioned above consider only two modes of urban transportation in the demand spillover context. Differently, we aim to stretch our investigation of the potential demand spillover during disruptions to a multi-modal horizon consisting of road, public transport and shared-bike users. The data-driven approach to identifying disruptive scenarios within the recorded demand data requires anomaly detection procedures for singling out instances of irregularity. There is rich literature on anomaly detection techniques and methods, spanning various fields of science [18]–[20]. Prasad *et al.* (2009) [21] define an anomaly as *a pattern that does not conform to expected normal behaviour*, and hence describe the anomaly detection as an effort to outline a normal behaviour range and detect any instance where data is outside this range.

In this paper, to automatically detect anomalies, we adapt an existing methodology from the state of the art [22], based on the definition of a spatialised demand signature (for mobile phone data), to multi-modal travel demand. Furthermore, we also develop an algorithm to pick out anomalous instances with a potential for demand spillover. Then, we dive more deeply into analysing specific scenarios of disruptive events to understand the multi-modal demand dynamics better.

III. DATA

Floating Car Data (FCD): The FCD has been provided by the *Autoroutes Traffic* company. The data are stored as daily datasets for 2019 and include timestamped geo-localisation data collected via GPS from moving vehicles. Each observation contains the speed for each moving vehicle ID in *km/h*, its direction and the map-matched link identifier from the road network topology, with a 30-seconds average observation frequency. The daily datasets are merged to form the general FCD dataset, denoted by D_{Car} . To get a proxy corresponding to demand, we consider the number of observations representative of car presence on the road network.

One limitation of this assumption is that a low number of observations can translate to lower demand for car use; however, a higher number of observations on the road network could also mean congestion. Additionally, the number of tracked floating cars corresponding to a roughly estimated 3% to 12% of the whole car park of the city, is a known limitation for this dataset. However, as shown in Section V, the available sample has proved to be sufficiently sensitive concerning the purpose of highlighting demand spillover phenomena.

Ticketing data: Lyon's public transport system consists of underground metro, funiculars, tramways and bus lines. Passengers must validate their tickets before entering metro and funicular stations, and before boarding on buses and trams. The dataset of 2019's recorded validations for Lyon has been provided by the *Keolis* company and is denoted as D_{PT} in the following. D_{PT} contains the aggregated number of hourly validations per line for each mode in 2019. It should be noted that metro and funicular validations were recorded as a single mode in the public transport dataset.

Bike Sharing Data: Lyon has a system of dock-based shared bikes with stations scattered across the city. The dataset at our disposal includes the information mentioned above for 2019. This dataset denoted as D_{Bike} , provided by the *JCDecaux* company, represents the shared-bike trips and includes the origin and the destination stops and timestamps for the retraction and the return of the bicycle, respectively indicating the start and the end of the trip. As we are concerned with the demand, we only use the retractions and their corresponding timestamps for our analyses.

It needs to be mentioned that bike-sharing accounts for only a quarter of daily bike trips in Lyon. Additionally, each bike station has a limited number of racks, meaning some stations might be empty for some hours, putting a cap on the supply side for shared bikes.

IV. METHODOLOGY

This section presents our proposed framework for identifying moments in time when travel demand on each mode diverges significantly from the signature, and for detecting instances with a potential inter-modal demand spillover. The next four steps detail our methodology.

Step 1 - Data pre-processing for multi-modal demand reconstruction: We transform the datasets at our disposal into a unified format and merge them into one single dataset. In particular, each of the input datasets D_{Car} , D_{PT} , and D_{Bike} are pre-processed by aggregating the provided observations to an hourly basis, selected as the common temporal granularity of our final unified dataset, denoted as D_{demand} .

This unification is carried out on the foundation of a few assumptions. First, we use the number of network-wide hourly retractions of shared bikes as an indicator of shared-bike demand. Second, we associate the network-wide hourly number of ticketing validations for public transport modes with the hourly demand for the respective mode. Third, utilising the FCD data, we consider the hourly number of observations in the dataset as the city-wide number of moving cars on the road network. Such values are thus considered as hourly counts of the demand for each mode. The final unified and pre-processed dataset can be denoted as $D_{demand} = \{N_t^q\}$, where N_t^q represents the observed amount of demand for mode q on the generic 1-hour time slot t from the time span of data availability, and $q \in \mathbf{Q} = \{bus, tram, metro, bike, car\}$.

Step 2 - Signature extraction: In this paper, similarly to the approach from [22] for mobile phone data, we consider a weekly-hourly temporal support for the computation of the signature from historical data. In other words, the signature is a compressed filtered representation on 24×7 time slots of the observed travel demand over a given observation period. Differently from [22], we propose distinct monthly signatures to avoid mixing seasonal travel behaviour. We then propose the following formal definition of signature, which denotes *the normal or expected range of travel demand* for a given transport mode at a specific time slot.

In our temporal support (m, w, h) for the computation of the signature, $m \in \mathbf{M}$, represents the month variable from

an ordered set of selected months \mathbf{M} ; $w \in \mathbf{W}$, represents the day of the week variable from an ordered set of selected week days \mathbf{W} , and $h \in \mathbf{H}$, represents the hour of the day variable from an ordered set of selected hours \mathbf{H} . It is worth noting that the (m, w, h) support identifies a set of time slots that will be considered for aggregation during the computation of the signature. As an example from our D_{demand} dataset, if $m = March$, $w = Monday$ and $h = 10$, the support (m, w, h) will correspond to the set of all the time slots related to 10:00 - 10:59 on every Monday of March 2019.

Based on the temporal support (m, w, h) and transport mode $mode \in \mathbf{Q}$, the signature element $S_{(m,w,h)}^q$ is defined as:

$$S_{(m,w,h)}^q = (\mu_{(m,w,h)}^q \pm \lambda_{(m,w,h)}^q) \quad (1)$$

where $\mu_{(m,w,h)}^q$ represents the average of the demand counts for the mode q for each weekday of the month; and $\lambda_{(m,w,h)}^q$ represents the range amplitude of the signature. We consider the range amplitude of the signature as a product of the hourly standard deviation $\sigma_{(m,w,h)}^q$.

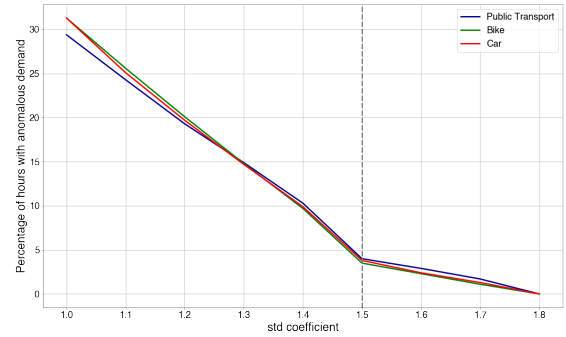


Fig. 1: Percentage of anomalous hours based on the standard coefficient

To define the signature range amplitude, we performed a sensitivity analysis on the percentage of hours that would fall outside said range. We adopted a heuristic approach for determining the standard deviation coefficient covering major disruptive events without leaving too much noise behind. We opted for a knee/elbow point in our sensitivity graph [23]. With this approach, as shown in Fig. 1, the standard deviation coefficient of 1.5 at the elbow point corresponds to a confidence interval of around 96% in all datasets. Our sensitivity analysis also confirms a Gaussian distribution for distances of counts from their respective means for each mode. The amplitude of range $\lambda_{(m,w,h)}^q$ is thus defined as $1.5 \times \sigma_{(m,w,h)}^q$.

Based on the previous definitions, the final signature for a given mode q on the reference time span induced by definition of the ordered sets $\mathbf{M}, \mathbf{W}, \mathbf{H}$ is thus:

$$S^q = \left|_{m \in \mathbf{M}, w \in \mathbf{W}, h \in \mathbf{H}} S_{(m,w,h)}^q \right. \quad (2)$$

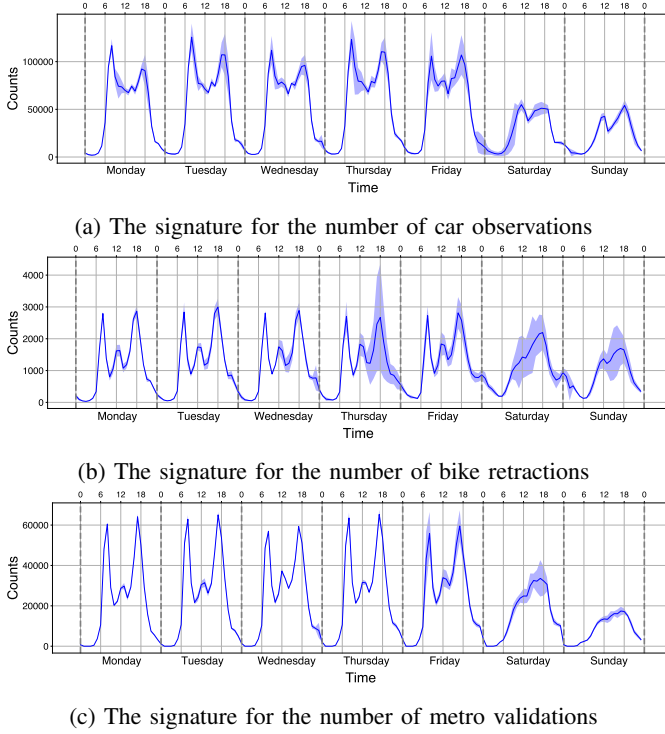


Fig. 2: The weekly signature of counts and observations for March 2019

where the $\left| \right|$ operator denotes the temporally sorted concatenation of the elements it is applied to.

Fig. 2, as an example, represents the signature for car observations, bike retractions, and metro validations for March 2019, when $\mathbf{M} = \{\text{March}\}$, $\mathbf{W} = \{\text{Monday}, \dots, \text{Sunday}\}$, $\mathbf{H} = \{00, \dots, 23\}$. For each mode q , the signature demonstrated in these figures includes the hourly average count $\mu_{(m,w,h)}^q$ and the amplitude $\lambda_{(m,w,h)}^q$ on each support (m, w, h) from the time span. It is worth noting that the signature range for each mode changes hourly, as it corresponds to the standard deviation of the hourly-weekly demand counts on that month. Therefore, greater demand fluctuations in certain weekday-hours result in wider signature ranges. Rainfall on Saturday March 2nd, Thursday March 14th, and Sunday March 17th has reduced shared-bike retractions and widened the signature range, as seen in Fig. 2b.

Step 3 - Anomaly detection: We label every count N_t^q from D_{demand} with an anomaly indicator, denoted as θ_t^q , set to 0 if N_t^q belongs in the corresponding signature range $S_{(m,w,h)}^q$. The indicator is set to 1, if the count number is larger than the higher edge of the signature, and -1, if it is lower than the lower edge of the range. The resulting dataset, denoted by D_θ , represents the hourly multi-modal demand record of our time range, including the anomaly indicator $\theta_{(m,w,h)}^q$ and filtered over the time span induced by the selection of $\mathbf{M}, \mathbf{W}, \mathbf{H}$. Algorithm 1 shows the pseudo-code for generating this indicator.

Algorithm 1 Anomaly detection

```

1: Input:  $D_{demand}, \mathbf{M}, \mathbf{W}, \mathbf{H}$ 
2: Output:  $D_\theta$ 
3:  $D_\theta \leftarrow \emptyset$ 
4: for  $N_t^q \in D_{demand}$  do
5:   extract  $(m, w, h)$  from  $t$ 
6:   if  $(m, w, h) \notin \mathbf{M} \times \mathbf{W} \times \mathbf{H}$  then
7:     continue ▷ skip to next iteration
8:   if  $N_t^q > \mu_{(m,w,h)}^q + \lambda_{(m,w,h)}^q$  then
9:      $\theta_t^q = 1$ 
10:  else if  $N_t^q < \mu_{(m,w,h)}^q - \lambda_{(m,w,h)}^q$  then
11:     $\theta_t^q = -1$ 
12:  else
13:     $\theta_t^q = 0$ 
14:  end if
15:   $D_\theta \leftarrow D_\theta \cup (N_t^q, \theta_t^q)$ 
16: end for
17: return  $D_\theta$ 

```

Step 4 - Detection of anomaly instances with potential inter-modal spillover: After the production of D_θ , we define another indicator ζ_t to identify anomalous hourly time slots t with an inter-modal spillover potential. The ζ_t indicator is a binary indicator defined by inspecting D_θ over an observation time period T . ζ_t is considered to be non-zero for anomalous hourly time slots exhibiting, simultaneously, opposite values (1 and -1) of the θ_t^q anomaly indicator for *at least* one pair of modes (q, r) . The rationale behind such an indicator is that the presence of a spillover during an anomaly shall translate into a gain of travel demand for one mode and a loss for another one, both with an amplitude beyond normal ranges for each of the two involved modes. Algorithm 2 formally describes, in pseudo-code, how the final dataset D_ζ , including the potential spillover information is produced.

Algorithm 2 Potential multi-modal demand spillover detection

```

1: Input:  $D_\theta, T, \mathbf{Q}$ 
2: Output:  $D_\zeta$ 
3:  $D_\zeta \leftarrow \emptyset$ 
4: for  $t \in T$  do
5:    $\zeta_t \leftarrow 0$ 
6:   for  $(i, j) \in \mathbf{Q} \times \mathbf{Q} - \{i\}$  do
7:     Retrieve  $(N_t^i, \theta_t^i)$  and  $(N_t^j, \theta_t^j)$  from  $D_\theta$ 
8:     if  $\theta_t^i = -\theta_t^j$  then
9:        $\zeta_t \leftarrow 1$ 
10:      break
11:    end if
12:  end for
13:   $D_\zeta \leftarrow D_\zeta \cup (t, \zeta_t)$ 
14: end for
15: return  $D_\zeta$ 

```

V. RESULTS

In order to evaluate the capability of our framework in detecting potential inter-modal demand spillover during disruptions, we analyse the D_ζ dataset, by taking into account, as ground truth, the recorded weather data for Lyon, as well as local news available over the timeframe of interest. Our data did not track the users' potential modal change decisions under disruptions, so the conclusion of inter-modal demand spillover with the same passengers remains a possible hypothesis.

We mostly ignore the first few hours of the day, as the low number of counts and observations results in high deviance, and consequently in positive spillover indications. We only

consider instances between 6:00 and 24:00 (the hours from 00:00 to 5:59 are filtered out from T , used as input to Alg. 2).

Among instances with positive spillover indicator ζ_t , we identified more than ten cases and verified them with ground truth. These events included terrorist attacks, precipitation-induced disruptions, large-scale social events, and public holidays. As these disruptive events differed in their affected mode, duration, time of occurrence, nature and spatial scope, their spillover dynamics also varied. Although diverse, these dynamics demonstrated similar patterns too. For instance, heavy precipitation was usually followed by a demand decrease in shared bikes and an increase in other modes, while the changes were dissimilar based on the rainfall's time and duration. In this section, as examples, we provide three distinct cases of potential spillover cases and their progression of demand dynamics during their corresponding disruptive event.

In addition to the anomaly indicator θ_t^q , we defined a continuous variable δ_t^q to calculate a standardised deviance of each count N_t^q from its corresponding average $\mu_{(m,w,h)}^q$. This variable, formulated in Eq. 3, is used in producing the radar chart plots proposed later in the section.

$$\delta_t^q = \frac{N_t^q - \mu_{(m,w,h)}^q}{\sigma_{(m,w,h)}^q} \quad (3)$$

Fig. 3 demonstrates the progression for multi-modal dynamics of standardised demand counts during said detected events. For each day, a 5-hour portion is selected to showcase dynamics during disruption hours. Each hour is exhibited with a radar chart, with transport modes being represented on the angular axis, and the demand deviance of the corresponding hour from the normal signature δ_t^q on the radial axis. The vertical alignment of hourly plots in the figure displays the progress for the multi-modal relationship of demand deviance from the signature through disruption hours. The upper and lower limits of the signature are also illustrated in the plots with light and dark grey polygons, respectively.

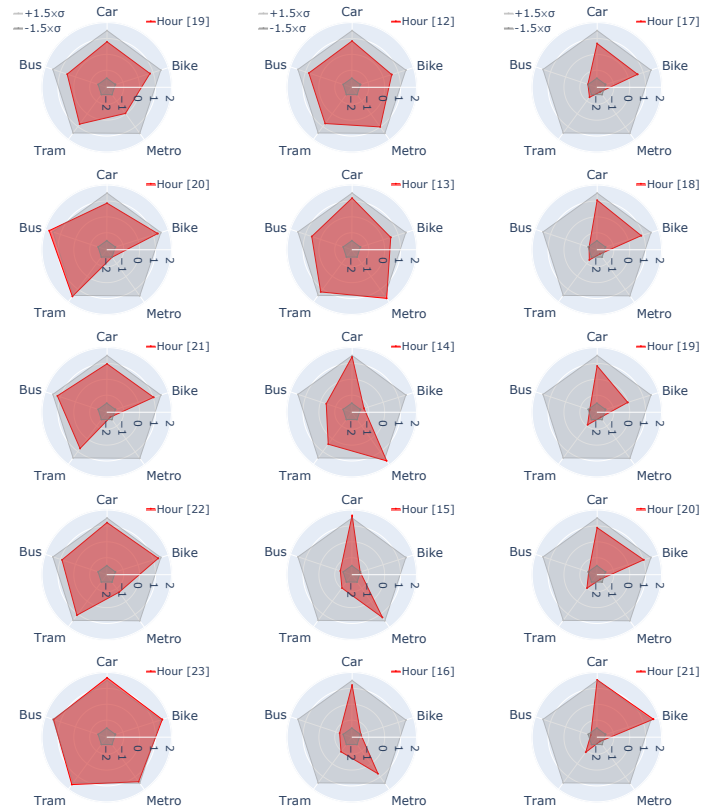
A. Terrorist Attack

On May 24th 2019, a bomb exploded in a busy central street in Lyon at 17:40, leading to the temporary closure of three central metro stations, of which one was an interchange station connecting two of the four metro lines.

Fig. 3a shows the deviation of demand counts for different modes through 5 hours following the incident. It appears reasonable to speculate that public transport users had to switch to other modes as their primary mode was unavailable. The immediate increased deviance from signature in bus and tram validations after the incident backs up this hypothesis.

B. Weather Induced Disruption

On Saturday, June 15th 2019, a high volume of precipitation was observed through our recorded weather data. Rainfall started from noon and continued until around 16:00. Fig. 3b represents a 5-hour progression of multi-modal deviance from signature demand, starting from noon. The plots showcase



(a) May 24th 19:00 to 23:59 (terrorist attack) (b) June 15th 16:59 to 21:59 (heavy rainfall) (c) December 8th 17:00 to 21:59 (festival of lights)

Fig. 3: The progression of Multi-modal demand dynamics during disruptive events

a potential spillover instance after 15:00, where a sharp decrease among shared-bike retractions is illustrated alongside increased metro validations and car observations. We thus hypothesize that under the precipitation condition, usual shared-bike users turn to other modes of transport, specifically metro and personal cars in this case. Towards the evening, a demand decrease in all public transport modes is observable compared to the expected demand. This decrease can be explained by the weather-induced cancellation of leisure trips, which usually take up an essential portion of urban travel on a typical Sunday afternoon.

C. Large-scale Community Event

Every year on December 8th, the Festival of Lights takes place in the city of Lyon, with major shows being held in the city's historic centre. On the afternoon of December 8th, 2019, passengers were able to use Lyon's metro for free for the rest of the day. Therefore, no metro validations were recorded after 16:00 that day. Additionally, a few bus lines paused their daily routes around the city's centre, as some streets were closed for the festival.

As Fig. 3c illustrates 5 hours of free metro service from 17:00 onward, a change in demand dynamic is visible on the

radar plots. The counts for public transport modes are under the normal range, while car and bike counts have increased. We hypothesise that the free service of the metro fueled the noticeable decrease in demand for other modes of public transport. It is worth mentioning that despite an initial relative decrease in the counts for shared bikes, the relative number of retracted Velo'v bikes significantly increased in this day's final hours, which surging return trips from the shows can explain.

VI. CONCLUSION AND PERSPECTIVES

In this paper, we explored the network-wide multi-modal demand dynamics under disruptions. We unified multi-source data for Lyon, merged them into one, and assigned indicators for detecting anomalies in an hourly-based structure. Among the detected anomalies, we identified the instances with potential inter-modal demand spillover and scanned them with recorded real-life events (weather and news) used as ground truth. We presented three identified instances to paint examples of our method's functionality on real data.

Contrary to the literature on travel behaviour response to disruptions, we have developed a method to analyse the demand dynamics of several transportation modes simultaneously. By providing a straightforward data-driven monitoring approach, this method demonstrates the capacity to detect anomaly instances in a network-wide scope of demand. It also lets us dive deeper into exploring the effects of various disruption scenarios on multi-modal travel demand. As our results suggest that different forms of disruption bring about different multi-modal demand dynamics; the methodology is serviceable for a scenario-based multi-modal analysis of disruption travel behaviour.

We plan to continue analysing the multi-modal dynamics of travel demand under disruptions. Our next direction will be dedicated to classifying disruption types based on their effects on multi-modal demand. Building on this paper's approach, where we individually matched the detected scenarios to the ground truth, we plan to develop machine-learning techniques to identify clusters of multi-modal demand counts in our future direction. We also consider to develop data-driven methods to forecast possible inter-modal demand spillover under various contextual changes such as extreme weather events.

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REFERENCES

- [1] Timothy F. Welch and Alyas Widita. Big data in public transportation: a review of sources and methods. <https://doi.org/10.1080/01441647.2019.1616849>, 39(6):795–818, 11 2019.
- [2] Wolfgang Burgholzer, Gerhard Bauer, Martin Posset, and Werner Jamernegg. Analysing the impact of disruptions in intermodal transport networks: A micro simulation-based model. In *Decision Support Systems*, volume 54, pages 1580–1586, 3 2013.
- [3] Greg Marsden and Iain Docherty. Insights on disruptions as opportunities for transport policy change. *Transportation Research Part A: Policy and Practice*, 51:46–55, 2013.
- [4] Sonia Adel , Sabine Tr fond-Alexandre, Corinne Dionisio, and Pierre Alain Hoyau. Exploring the behavior of suburban train users in the event of disruptions. *Transportation Research Part F: Traffic Psychology and Behaviour*, 65:344–362, 8 2019.
- [5] Alice Consilvio, Angela Di Febraro, Valentina Moretti, and Nicola Sacco. Design of collaborative multimodal strategies for disruption management in urban railway systems. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems, ITSC 2020*. Institute of Electrical and Electronics Engineers Inc., 9 2020.
- [6] Shanjiang Zhu, Hamza Masud, Chenfeng Xiong, Zhuo Yang, Yixuan Pan, and Lei Zhang. Travel behavior reactions to transit service disruptions: Study of metro safetrack projects in Washington, D.C. *Transportation Research Record*, 2649(1):79–88, 2017.
- [7] Hannah Budnitz, Lee Chapman, and Emmanouil Tranos. Better by bus? Insights into public transport travel behaviour during Storm Doris in Reading, UK. *Weather*, 73(2):54–60, 2 2018.
- [8] Xinyuan Zhang and Nan Li. Characterizing individual mobility perturbations in cities during extreme weather events. *International Journal of Disaster Risk Reduction*, 72:102849, 4 2022.
- [9] Simon Lepage and Catherine Morency. Impact of Weather, Activities, and Service Disruptions on Transportation Demand. <https://doi.org/10.1177/0361198120966326>, 2675(1):294–304, 11 2020.
- [10] Jianxi Gao, Baruch Barzel, and Albert L szl  Barab si. Universal resilience patterns in complex networks. *Nature*, 530(7590):307–312, 2 2016.
- [11] Duy Q. Nguyen-Phuoc, Graham Currie, Chris De Gruyter, and William Young. How do public transport users adjust their travel behaviour if public transport ceases? A qualitative study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 54:1–14, 4 2018.
- [12] N. Job A. Van Exel and Piet Rietveld. Public transport strikes and traveller behaviour. *Transport Policy*, 8(4):237–246, 10 2001.
- [13] N. J.A. van Exel and P. Rietveld. When strike comes to town... anticipated and actual behavioural reactions to a one-day, pre-announced, complete rail strike in the Netherlands. *Transportation Research Part A: Policy and Practice*, 43(5):526–535, 6 2009.
- [14] Honghai Li, Xiaolei Ma, Xian Zhang, Xin Li, and Weihai Xu. Measuring the Spatial Spillover Effects of Multimodal Transit System in Beijing: A Structural Spatial Vector Autoregressive Approach. *Journal of Advanced Transportation*, 2020, 2020.
- [15] Panayotis G. Michaelides, Konstantinos N. Konstantakis, Christina Milioti, and Matthew G. Karlaftis. Modelling spillover effects of public transportation means: An intra-modal GVAR approach for Athens. *Transportation Research Part E: Logistics and Transportation Review*, 82:1–18, 10 2015.
- [16] Meead Saberi, Mehrnaz Ghamami, Yi Gu, Mohammad Hossein (Sam) Shojaei, and Elliot Fishman. Understanding the impacts of a public transit disruption on bicycle sharing mobility patterns: A case of Tube strike in London. *Journal of Transport Geography*, 66:154–166, 1 2018.
- [17] Yuanxuan Yang, Roger Beecham, Alison Heppenstall, Andy Turner, and Alexis Comber. Understanding the impacts of public transit disruptions on bikeshare schemes and cycling behaviours using spatiotemporal and graph-based analysis: A case study of four London Tube strikes. *Journal of Transport Geography*, 98:103255, 1 2022.
- [18] Monowar H. Bhuyan, D. K. Bhattacharyya, and J. K. Kalita. Network anomaly detection: Methods, systems and tools. *IEEE Communications Surveys and Tutorials*, 16(1):303–336, 3 2014.
- [19] Animesh Patcha and Jung Min Park. An overview of anomaly detection techniques: Existing solutions and latest technological trends. *Computer Networks*, 51(12):3448–3470, 8 2007.
- [20] Azzedine Boukerche, Lining Zheng, and Omar Alfandi. Outlier Detection: Methods, Models, and Classification. *ACM Computing Surveys*, 53(3), 6 2020.
- [21] Nadipuram R. Prasad, Salvador Almanza-Garcia, and Thomas T. Lu. Anomaly detection : A Survey. *Computers, Materials and Continua*, 14(1):1–22, 2009.
- [22] Angelo Furno, Marco Fiore, Razvan Stanica, Cezary Ziemlicki, and Zbigniew Smoreda. A Tale of Ten Cities: Characterizing Signatures of Mobile Traffic in Urban Areas. *IEEE Transactions on Mobile Computing*, 16(10):2682–2696, 10 2017.
- [23] Ville Satop a, Jeannie Albrecht, David Irwin, and Barath Raghavan. Finding a "kneedle" in a haystack: Detecting knee points in system behavior. In *Proceedings - International Conference on Distributed Computing Systems*, pages 166–171, 2011.